EXPLORING THE EFFECT OF UNEMPLOYMENT TOWARDS CRIME RATES

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Abstract. This project explores the potential effect that the unemployment rate has on the crime rate in the U.S. We estimate the impact of unemployment rate towards crime by each state in the U.S. We control our research by state-level and by year effects. We find significantly positive effects of unemployment on both violent crime rate and property crime rates. Our estimates suggest that the poverty rate is also a key element when analyzing both types of crime rates, and the police rate in each state are considerably significant. However, after a closer analysis of the power of unemployment, the unemployment rate is weakly related to property crime.

Key words. Econometrics, Unemployment, Crime

1. Introduction . Social scientists put forward much evidence on the question of whether the unemployment rate affects the number of crime activities occur. Crimes imposes tremendous costs on our society, with unemployment rates considered as a significant factor contributing to crime rates. According to the Federal Bureau of Investigation(FBI), In 2018, violent crime was down 3.3% from the 2017 number. Property crimes also dropped by 6.3%. In the meantime, according to the annual national unemployment rate decreased from 4.4% (2017) to 3.9% (2018). The concurrence of the decreases in both crime rates and unemployment rates implies that the enrichment in legal employment opportunity affects the declines in criminal activities. Researches about the unemployment-crime relationship between the 1960s and 1970s show that the unemployment rates and crime rates in the U.S. are positively correlated. The project aims to explore whether those findings and conclusions still hold 50 years later, and what are the potential effects that unemployment rate has on the crime rate. Besides, Bloomberg has released a report that U.S. has the probability of 29% to hit another recession within the next 12 months. [1]Historically, the unemployment rate would increase during the period of recession. Recession would not only bring instability to the economy, but also to the social order. The finding in unemployment and crime rates motivates the policymakers think if reducing unemployment will be one of the most effective ways to fight crimes and to remain the social stability.

2. Literature Review. Unemployment could affect the level of crime by changing people's prospects towards the relative costs and its benefits associated with other ways of gaining income and wealth. Becker suggests that when an individual commit to crimes, he would compare the expected benefit and its expected costs. If the expected benefit that individual valued outweighs its expected cost, he becomes more likely to engage in criminal activities. Whether individuals would engage in criminal activities depends on which side they value more on.[2] Melick believes that when the unemployment rate is high, which means that there is limited employment opportunities available, the opportunity cost of committing crime is relatively low.[3] Similarly, according to Raphael and Winter-ebmer , the unemployment rate has a strong effect criminal activities, especially on property crimes. As for violent crimes, such as robbery, they also have evidence that the unemployment rates could positively affect the economically motivated violent crime.[29] In other words, when the unemployment rate decreases, the violent crime will decrease accordingly. This is also supported by Nordin and Almén. In their study, they concluded that there is a significant association between long-term unemployment and violent crime. When reducing the unemployment level, the violent crime seems to decrease at the same time.[**?**]

As for income level, it is also an important determinant for criminal activities. According to Krohn, the income level is strongly correlated to the crime rate.[6] This conclusion is supported by Yildiz and Ocal.[7] Their research indicates that the increases in income individuals have decreased number of criminal activities, which means there is a negative relationship between the income people receive and the number of crimes occurs.

Besides, Yildiz and Ocal also believe that the clearance rate has a negative effect on the number of crimes. The clearance rate is calculated by dividing the number of crimes that are being laid by the total number of crimes that are recorded. In most cases, clearance rate is used as a measure of the number of crimes that are solved by the police. Similarly, Title and Rowe hold that same assumption that the clearance rate and the number of crimes are negatively correlated.[8]

3. Data. The cross-sectional data used in this project comprise a panel of 51 U.S states with observations from 2017-2018. Following Nordin, research has repeatedly demonstrated positive relationships between unemployment and property crime, while weaker relationship between unemployment and violence crime will be expected. To differentiate various crimes, we obtained violence crimes per 100k and property crimes per 100k from the "Crime in the United States by Region, Geographic Division, and State, 2017-2018" produced by Federal Bureau of Investigation(FBI).[9] [10] The unemployment rates by states were taken from "Unemployment Rates for States, Seasonally Adjusted" from Bureau of Labour Statistics.[11][12] The police rates were calculated by full-time law enforcement employees over state population. The data of full-time law enforcement employees is acquired from "Full-time Law Enforcement Employees by State" produced by FBI.[13] [14]Poverty rates are taken from "Poverty rate in the United States, by state" produced by Statista.[15] As for GDP per capita, it is from Per capita Real Gross Domestic Product (GDP) of the United States in 2017, by state and Per capita Real Gross Domestic Product (GDP) of the United States in 2018, by state by Statista. According to Schaefer, the definition of racial minority group is defined to be groups who are classified according to obvious physical characteristics, e.g. skin color.[16] Therefore, we used each state population minus white population to obtain the minority population and divided by state population. The data of state populations and race populations were taken from "Population Distribution by Race/Ethnicity" from the Kaiser Family Foundation.[17] [18] Lastly, the data of hispanic rates were obtained from State Population by Race, Ethnicity Data at Governing, whose data was formatted from 1-year American Community Survey estimates in U.S. Census Bureau.[19] The descriptive statistics are provided in Table 1.

Table 1: Descriptive Statistics for Violence Crime Rates and Explanatory Variables					
Variables	Mean	Standard Deviation	Median	Min	Max
log(VCper100k)	5.8580	0.4281	5.8790	4.7190	6.913
PCper100k	2330.0000	668.1870	2372.0000	1248.0000	4374.0000
Year	2018.0000	0.5025	2018.0000	2017.0000	2018.0000
UnmplyRt	3.9970	0.2280	4.0000	7.0000	2.4000
PoliceRt	0.0030	0.0009	0.0029	0.0014	0.0077
PovertyRt	0.1275	0.0303	0.1201	0.0660	0.2076
GDP_Per_Capita	31633	413312	62544	31633	3018337
MinorityRt	0.2770	0.1554	0.2400	0.0500	0.7900
HispanicRt	0.1206	0.1032	0.0981	0.0100	0.4900

FIG. 1. *Table 1*

The information of correlation among variables is provided in Table 2 below. According to the rule of thumb for correlations, if the correlation coefficient is greater than 0.8, then severe multicollinearity may be present. The presence of multicollinearity affects the precise effects of predictors and makes the predictions very sensitive to minor changes in the model[20]. In our variables, the correlation coefficient for MinorityRt and Hispanic Rt is 0.89, which is highly correlated. In the following modeling section, we will try to use the method of best subset selection to decide whether to drop one of two variables, either MinorityRt or HispanicRt. For the correlations between our dependent variables and independent variables, log(VCper100k) is positively correlated with unemployment rates, police rates, poverty rates, GDP_per_capita, minority rates, and Hispanic rates. For PCper100K (property crime rates per 100k population), it is positively correlated with unemployment rates, poverty rates, and minority rates. However, it is negatively correlated with year, police rate, GDP_per_capita, and Hispanic rates.

Table 2: Correlation Coefficients									
Variable	log(VCper100k)	*PCper100k*	Year	UnmplyRt	PoliceRt	PovertyRt	GDP_Per_Capita	MinorityRt	HispanicRt
log(VCper100k)	1.000								
PCper100k	0.731	1.000							
Year	n/a	-0.127	1.000						
UnmplyRt	0.499	0.443	-0.211	1.000					
PoliceRt	0.324	-0.079	0.071	0.126	1.000				
PovertyRt	0.404	0.410	0.315	0.396	0.036	1.000			
GDP_Per_Capita	0.054	-0.107	0.429	-0.020	0.060	0.184	1.000		
MinorityRt	0.554	0.008	-0.257	0.405	0.3	0.144	0.021	1.000	
HispanicRt	0.166	-0.028	-0.079	0.128	0.064	0.056	0.241	0.890	1.000

FIG. 2. *Table 2*

Before building linear regression models, we also check the normality of our dependent variables: log(VCper100k) and PCper100k. Graphs are shown below:

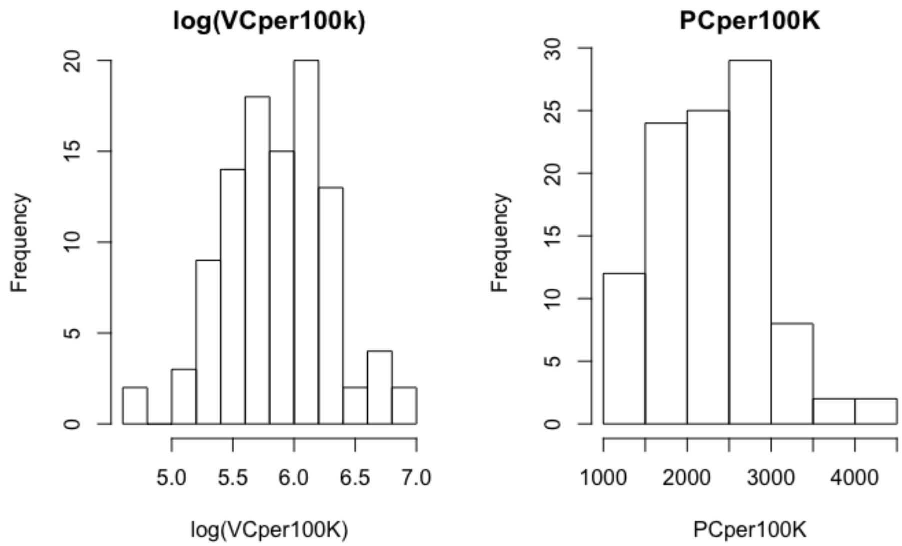

FIG. 3. *Normality of Response Variables*

The left graph demonstrates an approximately symmetrical bell shape, which indicates that the dependent variable log(VCper100k) is normally distributed. The right graph also shows an approximately normal bell shape while it skews right. In this case, there is no clear center point on a right-skewed graph.

4. Empirical Results. In this section, we present our results. First, we present OLS estimates of the crime-unemployment effects for violence crime rates. Then, we present OLS estimates for crime-unemployment effects for property crime rates.

4.1. Simple linear regression model for violence crime rates and unemployment rates.

$$\log(VCper100k) = \beta_0 + \beta_1 UmployRt + \epsilon$$

Table 3: (OLS) Estimated Coefficient for log(VCper100k= β_0 + β_1 UmployRt			
	Coefficient	Standard Error	T-calc
Intercept	-51.94	64.99	-0.799
UmployRt	108.99	15.86	6.872

FIG. 4. *Table 3*

Table 3 presents the OLS results of the simple linear regression between unemployment rates and the log of violence crime rates per 100,000 population, which is a preliminary overview of the linear relationship between violence crime and unemployment. Holding other factors constant, for 0.01 unit increase unemployment rates, there will be a correspondingly 108.99% increase in violence crimes per 100,000 population. In addition, the p-value of the F-test for UmployRt is $5.487 * 10^{-10}$, which indicates that unemployment is a statistically significant predictor. However, since at this point, we are not sure if there are other factors affecting the violence crime rates with unemployment based on our correlation table. A previous study by Nordin suggests that a more selective or different group faces the risk of committing to violence crimes and that long-term unemployment is superior in identifying this marginal group. We ran a multiple linear regression model attempting to identify this group.

4.2. Multiple linear regression model for violence crime rates and unemployment rates.

$$\log(VCper100k) = \beta_0 + \beta_1 year + \beta_2 UnemployRt + \beta_3 PoliceRt + \beta_4 PovertyRt$$

$$+\beta_5 GDP_p er_c apita + \beta_6 MinorityRt + \beta_7 HispanicRt + \epsilon$$

Table 4: (OLS) Estimated Coefficient				
	Coefficient	Standard Error	T-calc	Pr(>|t|)
Intercept	$6.397 * 10^1$	$0.1.715 * 10^2$	0.373	0.72873
year	-31.57	0.085	-0.348	0.72873
UmployRt	0.1349	0.0467	3.02	0.00325 **
PoliceRt	$0.1.263 * 10^2$	$3.853 * 10^1$	3.278	0.00146 **
PovertyRt	3.62	1.323	2.736	0.00743 **
GDP-Per-Capita	$4.674 * 10^{-9}$	$8.885 * 10^{-8}$	0.053	0.95816
MinorityRt	0.5856	0.264	2.218	0.02894 *
HispanicRt	-81.03	0.3387	-0.002	0.99819

FIG. 5. *Table 4*

Table 4 shows that UmployRt,PoliceRt, PovertyRt, and MinorityRt has statistical significance on the crime violence rates based on the p-value for each t test. The R2for F test is 0.4493, which means that 44.93% of total variation in log(VCper100k)can be attributed by the variations in our explanatory variables. However, the correlation table raised our attention that there is severe multicollinearity between MinorityRt and HispanicRt, and the p-value in the t test is telling us that HispanicRt may be insignificant. To have a more comprehensive and convincing selection of predictors, we adopted the method of best subset to conduct feature selection with R. The best subsets regression is a model selection approach that consists of testing all possible combinations of the predictor variables, and then selects the best model according to some statistical criteria.[21] Based on the criteria of adjusted R^2, Mallow's C_p, and Bayesian information criterion(BIC), we chose the model without HispanicRt. Output of best subset regression is shown in Table 5.

Table 5 : Output for Best Subset Regression

	Intercept	Year	UnmplyRt	PoliceRt	PovertyRt	GDP_Per_Capita	MinorityRt	HispanicRt	rsq	adjr2	cp	bic
1	1	0	1	0	0	0	0	0	0.26	0.28	27.4	-22
2	1	0	1	1	0	0	0	0	0.36	0.35	12.7	-32
3	1	0	1	1	1	0	0	0	0.41	0.39	6.58	-35
4	1	0	1	1	1	0	1	0	0.45	0.43	2.13	-38
5	1	1	1	1	1	0	1	0	0.45	0.42	4	-33
6	1	1	1	1	1	1	1	0	0.45	0.42	6	-28
7	1	1	1	1	1	1	1	1	0.45	0.41	8	-23

FIG. 6. *Table 5*

Comparing models with 6 predictors and 7 predictors in the highlighted row, the model without HispanicRt has better performance with higher adjusted R^2, lower Mallow's C_p, and BIC. We were dropping predictor HispanicRt and rebuilt our OLS model:

$$\log(VCper100k) = \beta_0 + \beta_1 year + \beta_2 UnemployRt + \beta_3 PoliceRt + \beta_4 PovertyRt$$

$$+\beta_5 GDP_p er_c apita + \beta_6 MinorityRt + \epsilon$$

Table 6: (OLS) Estimated Coefficients				
	Coefficient	Standard Error	T-calc	Pr(>|t|)
Intercept	$6.400* 10^{1}$	$1.699* 10^{2}$	0.377	0.70719
year	-31.85	$8.421* 10^{-2}$	-0.351	0.72614
UmployRt	$1.349* 10^{-1}$	$4.443* 10^{-2}$	3.037	0.00309**
PoliceRt	$1.263* 10^{2}$	$3.827* 10^{1}$	3.301	0.00136**
PovertyRt	3.62	1.316	2.751	0.00712**
GDP-Per-Capita	$4.679* 10^{-9}$	$8.837* 10^{-8}$	0.053	0.95796
MinorityRt	$5.855* 10^{-1}$	$2.484* 10^{-1}$	2.357	0.02050*

FIG. 7. *Table 6*

Table 6 shows that UmployRt,PoliceRt, PovertyRt, and MinorityRt has statistical significance on the crime violence rates based on the p-value for each t-test. The R^2 for F test is 0.4493, which is the same with the model with HispanicRt. It verified the correctness of feature selection. Looking at the regression coefficients, our key explanatory variable unemployment has a coefficient of 0.1349, which means that for unemployment generate a positive effect on violence crime rates. To some extent, it answers our research question, a state with its increased unemployment rate will be expected to have higher violence rates. Poverty is also an important indicator of violence crimes. Besides, the rate of minority groups imposes a positive effect on violence crime rates, even though a previous study shows that there is little evidence of important racial and ethnic differences in either self-reported offending (frequency or variety) or officially based arrests leading to a court referral in the year preceding study enrollment. [22] It is worthy of attention that the police rate has an extremely large regression coefficient($1.263*10^2$), which brings up the problem of causation: whether it is more police officers leads to more violence crimes or more law enforcement officers are employed because there are a great number of violence crimes. We tend to the opinion that more police officers are employed in places that have higher crime rates with the exception that more police officers will decrease crime rates because research shows that more police will result in less crime.[31]

To validate the assumptions of this OLS model, we conducted the Breusch-Pagan test and residual analysis by residual diagnostic plots as below. The p-value of the Breusch-Pagan test is 0.1872, which satisfies the assumption of homoscedasticity. It is demonstrated in the Graph 3 that points are pretty symmetrically distributed, tending to cluster towards the middle of the plot and generally there is no clear pattern. As for the Q-Q plot, most of the points lie on y=x, which satisfies the assumption of normal error terms.

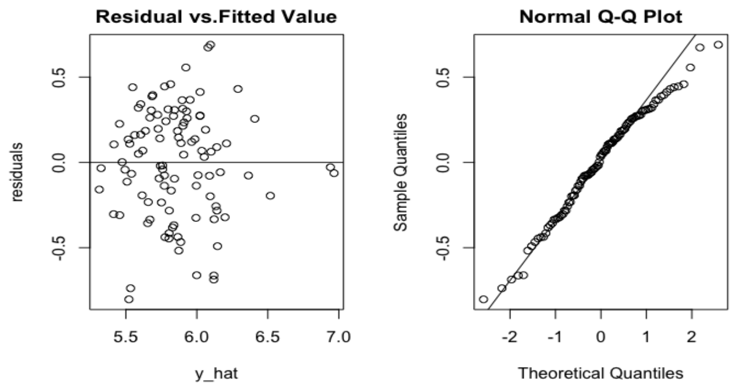

FIG. 8. *Residual Plots*

A research has revealed a positive association between unemployment and property crimes.[24] We want to verify whether it would apply to our cross-sectional data between 2017 and 2018 by OLS.

4.3. Simple linear regression model for property crime rates and unemployment rates.

$$PCper100k = \beta_0 + \beta_1 UmployRt + \epsilon$$

Table 7: (OLS) Estimated Coefficients			
	Coefficient	Standard Error	T-calc
Intercept	1029.41	270.23	3.809
UmployRt	325.49	65.94	4.936

FIG. 9. *Table 7*

Table 7 present the OLS results of the simple linear regression between unemployment rates and property crime rates per 100,000 population. Holding other factors constant, for 0.01 unit increase unemployment rates, there will be a correspondingly

325.49% increase in property crimes per 100,000 people. Moreover, the p-value of the F-test for UmployRt is 0.1959, which is against our initial expectation that unemployment is a statistically significant predictor for property crime rates. We preassumed that people who are out of employment are more likely to engage in property crimes gain money. In this case, there may be other factors that affect on the statistical significance of unemployment or superior to unemployment as predictors of property crimes. Therefore, we construct a multiple linear regression model.

4.4. Multiple linear regression model for property crime rates and unemployment rates.

$$PCper100k = \beta_0 + \beta_1 year + \beta_2 UnemployRt + \beta_3 PoliceRt + \beta_4 PovertyRt$$

$$+\beta_5 GDP_per_capita + \beta_6 MinorityRt + \beta_7 HispanicRt + \epsilon$$

Table 8: (OLS) Estimated Coefficient				
	Coefficient	Standard Error	T-calc	Pr(>|t|)
Intercept	1.285* 10^5	2.668* 10^5	0.481	0.631329
year	-64.135	1.323* 10^{-2}	-0.48	0.632345
UmployRt	8.89* 10^1	0.695	1.279	0.20411
PoliceRt	8.928* 10^4	5.996* 10^{-4}	1.489	0.139803
PovertyRt	7.686* 10^3	2.059* 10^{-3}	3.733	0.000324 ***
GDP-Per-Capita	-29.8	1.383* 10^{-4}	-1.866	0.065202
MinorityRt	1.718* 10^3	0.041	4.181	6.52e-05 ***
HispanicRt	-419.424	0.053	-0.78	0.437308

FIG. 10. *Table 8*

Table 8 shows the results of OLS for the model above. Similarly, owing to the presence of multicollinearity, we performed best subset regression on model (5). Output of the best subset regression is shown in Table 9.

Table 9 : Output for Best Subset Regression												
	Intercept	Year	UnmplyRt	PoliceRt	PovertyRt	GDP_Per_Capita	MinorityRt	HispanicRt	rsq	adjr2	cp	bic
1	1	0	0	0	0	0	1	0	0.27	0.27	26.7	-23.37
2	1	0	0	0	1	0	1	0	0.39	0.38	9.13	-36.16
3	1	0	0	0	1	1	1	0	0.42	0.4	5.4	-37.26
4	1	0	1	0	1	1	1	0	0.44	0.41	5.04	-35.08
5	1	0	1	1	1	1	1	0	0.45	0.42	4.91	-32.72
6	1	0	1	1	1	1	1	1	0.45	0.42	6.23	-28.83
7	1	1	1	1	1	1	1	1	0.45	0.41	8	-24.45

FIG. 11. *Table 9*

Comparing models with 5 predictors and 5 predictors in the highlighted row, the model without HispanicRt has better performance with same adjusted R^2, lower Mallow's C_p, and lower BIC. We eliminated the predictor HispanicRt and rebuilt our OLS model, Table 10 shows the results for our model without HispanicRt:

$$PCper100k = \beta_0 + \beta_1 year + \beta_2 UnemployRt + \beta_3 PoliceRt + \beta_4 PovertyRt$$

$$+\beta_5 GDP_p er_c apita + \beta_6 MinorityRt + \epsilon$$

Table 10: (OLS) Estimated Coefficient				
	Coefficient	Standard Error	T-calc	Pr(>|t|)
Intercept	$1.471 * 10^5$	$2.652 * 10^5$	0.554	0.5805
year	-734.573	$1.315 * 10^2$	-0.553	0.58145
UmployRt	$8.961 * 10^1$	$6.937 * 10^1$	1.292	0.19955
PoliceRt	$9.181 * 10^4$	$5.975 * 10^4$	1.537	0.1277
PovertyRt	$7.699 * 10^3$	$2.055 * 10^3$	3.747	$3.07 * 10^{-4}$***
GDP-Per-Capita	-29.98	$1.380 * 10^{-4}$	-1.883	0.062748
MinorityRt	$1.614 * 10^3$	$3.879 * 10^2$	4.161	$6.97 * 10^{-5}$***

FIG. 12. *Table 10*

After we dropped HispanicRt, the adjusted R^2 increases from 0.4118 to 0.4142, and the magnitude of regression coefficient increases. It is shown in table 10 that property crime rates have strong linear relationship with poverty rates and minority rates. Concerned about the problem of heteroskedasticity in our model, we performed Brusch-Pagan test again and found that the p-value equals 0.01083, which reveals our model presents heteroskedasticity. According to Stock and Watson, panel data regression with heteroskedasticity can be fixed by using heteroskedasticity-robust standard errors.[25] In the Huber-White's Robust Standard Errors approach, the covariance matrix of the coefficient matrix is calculated by:

$$Var(\beta) = (X^T X)^{-1} X^T S X (X^T X)^{-1}$$

where S is the covariance matrix of residuals under the assumption of $\mathrm{E}(u_i) = 0$. In order to calculate the standard error for the regression coefficients when there is heteroskedasticity, the sample variance of OLS estimator (under finite sample properties) is:

$$\begin{aligned} Var(\beta) &= Var[\beta + (X^{'}X)^{-1}X^{'}u] \\ &= E[(X^{'}X)^{-1}X^{'}uu^{'}X(X^{'}X)^{-1}] \\ &= (X^{'}X)^{-1}X^{'}E(uu^{'})X(X^{'}X)^{-1} \\ &= \sigma^2(X^{'}X)^{-1}X^{'}\omega X(X^{'}X)^{-1} \end{aligned}$$

Using the vcovHC( ) function from the sandwich package in R, we gained a new OLS with heteroskedasticity-robust standard errors. The output is shown in Table 11:

Table 11: Estimated Coefficient heteroskedasticity-robust standard errors

	Coefficient	Standard Error	T-calc	Pr(>|t|)
Intercept	$1.4705*10^5$	$3.0733*10^5$	0.4785	0.6333
year	-734.5427	$1.5233*10^2$	-0.4774	0.6341
UmployRt	89.661	$9.6597*10^1$	0.9227	0.356
PoliceRt	$9.1811*10^4$	$8.6152*10^4$	1.0657	0.2893
PovertyRt	$7.6991*10^3$	$2.457*10^3$	3.1336	0.0023 **
GDP-Per-Capita	-29.98	$2.1012*10^{-4}$	-1.2364	0.2194
MinorityRt	$1.6137*10^3$	$3.0710*10^2$	5.2546	9.08*10-7 ***

FIG. 13. *Table 11*

We can notice that the regression coefficients mostly do not change while the standard error increase. It is shown in the results that year does not have a significant effect on the crime, which means that there is not a big variation between 2017 and 2018. For our key explanatory unemployment rate, surprisingly it does not have statistical significance on property crime rates based on the criteria of big p-value. Concerning the performance of other variables in Table 11, police rates exert a positive effect on property crime with an incredibly large regression coefficient while with small statistical significance. The explanation for the positive relationship between police and crimes are similar to the one for violence crimes. The poverty rate exhibits a statistically significant positive effect on property rates. Since the income level is strongly correlated to the crime rate poverty results from low-income level is reasonable to generate a positive effect on property rates.[6] Also, property crimes are direct ways of obtaining money, property, and some other benefits, which are what people at poverty level lack of. When it comes to GDP_per_caipta, it has an extremely small negative regression coefficient and no statistical significance. An empirical result acquired by Carlos Bethencourt suggests that a negative relationship between property crime and per capita GDP exists with the poorest countries reporting the highest levels of property crime because of the effectiveness of crime control policies in areas with high per capita GDP, which echoes with our results.[26] The variable with the highest statistical significance in our model turned out to be minority rate. Holding other factors constant, for one unit increase in minority rate, the property crime will increase by 1,6137*103units. According to the arrested data collected by the FBI from 2017, 973,219 people were arrested because of property crimes, among which 657,574 are white people. It somehow violates our conclusion for the model that minority group is an essential indicator of property crime.

To validate other assumptions of our model, we conducted the residual analysis and some visualizations shown below:

As revealed in residual plots above, there is no clear pattern of residuals and most of the points lie on the y=x line in the Q-Q plots. Therefore, the assumptions of homoscedasticity and normality of error terms hold. It is observed that there are outliers in both tails, from which we imply that it is necessary to extend to robust regression for our model.

5. Concluding Remarks. In this project, we analyzed the relationship between the unemployment rate and the number of crimes reported. Our result shows that the

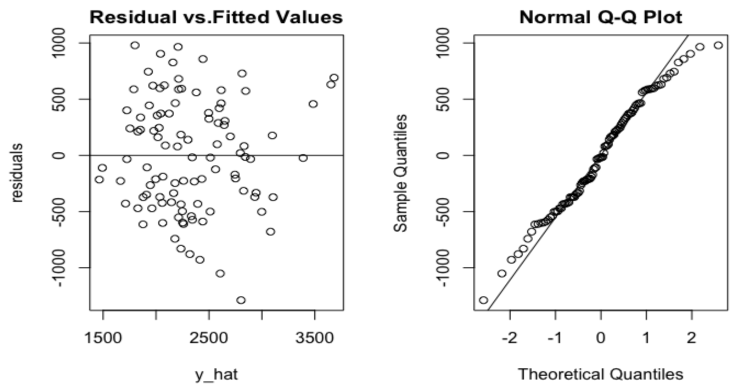

Fig. 14. *Residual Plots*

effect of unemployment is significant in terms of violent crime but is weakly correlated with property crime. The finding about the significant effect of unemployment on violent crime rate meets our expectations, especially when we are thinking about robberies. Unemployment places individuals in a situation that they do not have stable earnings to support their lives and families. Therefore, they might think of involving in criminal activities like what we have mentioned about robberies. However, surprisingly, statistics show that the effect of unemployment is insignificant in terms of property crime, which is on the opposite direction of our expectations and against many previous literature studies. Since if we think about being out of workplaces and having no income, when individuals decide to engage in criminal activities, they would prefer to break into others' property to find those illegal earnings.

This unusual phenomenon could be explained by the poverty rate in each state. The poverty rates in each state are strongly correlated with both types of crime rates, and it has more significant effects on property crimes. Compared to being unemployed, individuals who are under the poverty line are directly facing the problem of being unable to support their lives. Thus, instead of being involved in violence and hurting others, engaging in property crimes are more likely to satisfy their needs. Unlike our common sense that more police officers can reduce the crime rates in the area, we find that the police rate in each state is positively correlated with the crime rates. It would be the discussion between whether more police in the area leads to more crimes, or more police officers are employed because of the high crime rates within that area.

In addition, when estimating crime rates, the minority rate is one important element that should be taken accounted for. Differ from many previous studies, our statistic shows that the minority group has a positive effect on the crime rate, especially on the violent crime rate. This might be the problem of the panel dataset we used only contains two years of data. Thus, the future direction of the research would require us to obtain a dataset that has a wider range in terms of years.

Concerning the assumptions of linear regression models, our model presents the problem of omitted variable bias, which leads to biased estimates as it violates the exogeneity assumption of the Gauss–Markov theorem. Sieger mentions that "reverse causation may upwardly bias OLS estimates of the causal effect of unemployment on crime: as criminal activity reduces the employability of offenders, criminal activity may contribute to observed unemployment." Therefore, we will need to control for as many potential determinants of crimes as possible.[27] Sieger also suggests to instrument unemployment to decrease of reverse causation or other sources of endogeneity.[27] when we have panel data, the instrumental variable approach is a good means of identifying the link between crimes and unemployment, since omitted variables and measurement error can all lead bias in the OLS regression.[28] The failure of obtaining a comprehensive range of potentially significant variables on crime rates may cause a downward bias to the relationship between crime and unemployment. Many studies have proposed different options of instrumental variables for unemployment: military contracts and a state-specific measure of exposures to oil shocks[29], initial sectional composition of employment in each municipality with the national composition trends in employment[**?**], and state union membership rates[31]. These will be potential ways for us to instrument unemployment for its effect on crimes in the future.

We were thinking about using the price of petroleum (capita per barrel), and since we believe that petroleum use is necessary among all industries in terms of production costs and shipment costs, the price of petroleum could be one element that affect the unemployment rate in the U.S. The reason why we did include the price of petroleum in our model is because we only have a short panel data which only have 2 years of data. More importantly, the data for the 2018 petroleum prices are mostly planned to be in the public after the first quarter of 2020.

REFERENCES

[1] Picket,R, Et.al *AU.S. Recession Odds Steady as Stocks Reach Fresh Records.* Bloomberg.2019

[2] Becker, G. S. *Crime and Punishment: An Economic Approach.* The Journal of Political Economy, 76 (2): 169-217. 1968

[3] Melick,Matthew D. *The Relationship between Crime and Unemployment.* The Park Place Economist: Vol. 11.2003

[4] Raphael, S., and Winter-Ebmer, R. *Identifying the Effect of Unemployment on Crime.* SSRN Electronic Journal. doi: 10.2139/ssrn.145790.1999

[5] Nordin, M., and Almen, D. *Long-term unemployment and violent crime.* Economics, 52(1), 1–29. doi: 10.1007/s00181-016-1068-6.2016

[6] Krohn, M. D. *Inequality, Unemployment and Crime: A Cross-National Analysis* The Sociological Quarterly, 17(3), 303–313. doi: 10.1111/j.1533-8525.1976.tb00984.x, 1976

[7] YILDIZ, R., OCAL, O., YILDIRM, E. *The Effects of Unemployment, Income and Education on Crime.* International Journal of Economic Perspectives. 2013;7(2):32-40. 2013

[8] Tittle, C. R. and Rowe, A. R. *Certainty of Arrest and Crime Rates: A Further Test of the Deterrence Hypothesis.* Social Forces, 52(4), 455. doi: 10.2307/2576988. 1974

[9] FBI National Press Office. *Crime in the United States, 2017.* Federal Bureau of Investigation.Wahsington, DC: UCR.2018

[10] FBI National Press Office. *Crime in the United States, 2018.* Federal Bureau of Investigation.Wahsington, DC: UCR.2019

[11] U.S.Bureau of Labor Statistics. *Unemployment Rates for States, 2017 Annual Averages* Local Area Unemployment Statistics.2019

[12] U.S.Bureau of Labor Statistics. *Unemployment Rates for States, 2018 Annual Averages* Local Area Unemployment Statistics.2019

[13] U.S Department of Justice, Bureau of Justice Statistics, Criminal Justice Information Service Division. *Full-time Law Enforcement Employees by State,2017.* Wahsington, DC: UCR.2018

[14] U.S Department of Justice, Bureau of Justice Statistics, Criminal Justice Information Service Division. *Full-time Law Enforcement Employees by State,2018.* Wahsington, DC: UCR.2019

[15] Duffin,Erin *Poverty rate in the United States in 2018, by state.* Statista.2019

[16] Schaefer, Richard.T. *Racial and Ethnic Groups.* Pearson Education, pp 5-10.1993

[17] Kaiser Family Foundation *Population Distribution by Race/Ethnicity (Time Frame: 2017).* States Health Facts. 2018

[18] Kaiser Family Foundation *Population Distribution by Race/Ethnicity (Time Frame: 2018).* States Health Facts. 2019

[19] Governing *State Population By Race, Ethnicity Data.* https://www.governing.com/gov-

data/census/state-minority-population-data-estimates.html. 2018

[20] Gharibdousti, M. S Et,al. *Breast cancer diagnosis using feature extraction techniques with supervised and unsupervised classification algorithms.* Applied Medical Informatics, 41(1), 40–52. 2019

[21] Kassambara,Alboukadel. *Best Subsets Regression Essentials in R* Sthda, 2018

[22] Piquero, A. R., Brame, R. W. *Assessing the Race-Crime and Ethnicity-Crime Relationship in a Sample of Serious Adolescent Delinquents.* Crime Delinquency, 54(3), 390–422. 2008

[23] Lin,Ming-Jen. *More police, less crime: Evidence from US state data.* International Review of Law Economics, 29(2), 73–80.2009

[24] Mustard, David. *How Do Labor Markets Affect Crime? New Evidence on an Old Puzzle* Institute of Labour Economics, IZA DP No. 4856. 2010

[25] Stock,JAMES H.and Watson,MARK W. *Heteroskedasticity-Robust Standard Errors for Fixed Effects Panel Data Regression* Econometrica, Vol. 76, No. 1, 155–174.2008

[26] Bethencourt,Carlos *Crime and Social Expenditure: A Political Economic Approach.* Mimeo.2015

[27] Sieger, Philip. *Job Losses and Criminal Gains: Analyzing the Effect of Unemployment on Criminal Activity.* Annual Conference 2013 (Duesseldorf): Competition Policy and Regulation in a Global Economic Order 79929, Verein für Socialpolitik / German Economic Association.2013

[28] Levitt, Steven,D. *Alternative Strategies for Identifying the Link Between Unemployment and Crime.* Journal of Quantitatiûe Criminology, Vol. 17, No. 4. December 2001

[29] Raphael, S., and Winter-Ebmer, R. *Identifying the Effect of Unemployment on Crime.* SSRN Electronic Journal. doi: 10.2139/ssrn.145790.1999

[30] Oster,Anna and Agell,Jonas *Crime and Unemployment in Turbulent Times.* Journal of the European Economic Association, 5(4), 752.2007

[31] Lin,Ming-Jen *Does Unemployment Increase Crime? Evidence from U.S. Data 1974–2000* Vol. 43, no. 2, 2012, pp. 413–436. EBSCOhost, doi:10.1353/jhr.2008.0022.2012